WHAT DO INTEREST INVENTORIES MEASURE? THE CONVERGENCE AND CONTENT VALIDITY OF FOUR RIASEC INVENTORIES

BY

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THESIS

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ABSTRACT

Most interest inventories aim to measure the same core interest traits based on Holland’s (1997) RIASEC model. Despite the widespread use of RIASEC interest inventories, little is known about the extent to which these inventories actually measure the same core constructs and provide similar career recommendations to individuals. The current study investigates the convergent validity among four major interest inventories—the Self-Directed Search (SDS), the O*NET Interest Profiler (IP), the ACT Interest Inventory (UNIACT), and the Strong Interest Inventory (SII). Three methods were used to analyze different aspects of convergence: 1) correlated trait-correlated methods (CT-CM) model, 2) high-point code agreements, and 3) item content analysis. Results showed that, although RIASEC interest scores from the four inventories were highly correlated, the measures often gave respondents different high point codes that lead to divergent career recommendations. Moreover, item content analysis revealed that while the inventories measure some common basic interest dimensions, they also assess distinct peripheral basic interests. Integrating findings from these three unique perspectives, we put forth practical recommendations for constructing future interest inventories to increase convergence. We also discuss the importance of using multiple methods to investigate convergent validity, especially content analysis which provides foundational guidance for interpreting results from existing interest inventories.

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CHAPTER 1: INTRODUCTION

At some point in life, almost everyone takes an interest inventory. Interest inventories are widely used to help people make decisions in educational and occupational settings (Hanna & Rounds, 2020). Since the 1970's, Holland's (1973, 1985, 1997) RIASEC model has been used to assess and organize interest types in vocational interest inventories. The RIASEC model provides a theoretical framework that helps individuals understand their interests in six general domains: Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C). Despite the popularity of Holland's RIASEC model, few studies have compared what is being assessed by distinct inventories adopting the model. As a result, little is known about the convergent validity of RIASEC scores from different interest inventories.

Understanding the convergent validity among interest inventories is critical for both practice and research. In practice, individuals (and career counselors) often use RIASEC interest profiles to help focus career and educational exploration. Occupations are typically considered good fits when they have similar patterns of RIASEC scores to individuals. To work effectively on a large scale, this method of career matching requires that interest inventories bear similar reflections of the RIASEC constructs. If interest inventories do not converge on their representation of Holland's model, an individual could receive different RIASEC profiles from different inventories, and would therefore be pointed towards divergent careers. Convergent validity is also critical for research purposes. The RIASEC types are complex, multidimensional constructs that each cover a range of basic interests (Su et al., 2019). For cumulative knowledge to progress about the structure, development, and correlates of vocational interests, it is essential that research findings are not contingent on the measure used in particular studies.

In this study, we investigate evidence for convergent validity among four widely used interest inventories using both statistical and content-based approaches. Specifically, we examine: (a) the Self-Directed Search (SDS; Holland, 1994), (b) the O*NET Interest Profiler Short Form (IP; Rounds et al., 2021), (c) the ACT Interest Inventory (UNIACT-R; ACT, 1995) and (d) the Strong Interest Inventory (SII; Harmon et al., 1994). Our study has three major aims. First, we examine interest score convergence using a correlated trait-correlated method (CTCM) model. Second, we build on the CTCM approach to assess convergence in terms of RIASEC high-point code agreements, a central issue for career counselling. Third, we systematically examine item content coverage using basic interests, revealing how differences in item content can lead to different interpretations of interest scores. Across analyses, we advance theoretical understanding of what is actually being measured by different RIASEC inventories. Ultimately, both practitioners and researchers can benefit from a deeper understanding of the shared interest space among different measures.

Assessing Convergence Among RIASEC Interest Inventories

Holland's RIASEC model[1] provides a unified classification system for vocational interests and occupational environments (Campbell & Borgen, 1999; Campbell & Holland, 1972). The simplicity of the RIASEC model has led to its wide applications in career guidance, organizations (Su & Nye, 2017), and educational settings (e.g., the World of Work curriculum, Prediger & Swaney, 2004). The RIASEC model is also the dominant measurement framework for vocational interest research. For example, RIASEC interests predict people's life goals (Stoll et al., 2020), influence academic and career choices (Hanna & Rounds, 2020; Usslepp et al., 2019), and predict job performance, satisfaction, and career success (Hoff et al., 2020; Nye et al.,

[1] Table 7 in the supplementary material summarizes Holland (1985)'s descriptions of each RIASEC type and gives example activities and occupations.

2012, 2017; Rounds & Su, 2014; Van Iddekinge et al, 2011). Holland's model also serves as the predominant framework for integrating interests with other individual difference domains, such as personality (Mount et al., 2005) and cognitive ability (Passler et al., 2015)

With the widening application of Holland's model, numerous measures have been developed to assess the RIASEC categories. However, *a key question remains*: do different interest inventories provide people with the same results and consequently similar information about career options? Our study uses Holland's theoretical model, and corresponding basic interests (Su et al., 2019), to investigate evidence for convergent validity in three complementary ways. The first, and most often used approach, is based on correlations of RIASEC scores from different inventories. Statistical models based on these correlations can partition the separate influences of interest traits and inventory methods on RIASEC scores (Eid et al., 2006). The second approach examines a more critical issue for practice: whether different inventories assign similar high-point codes (i.e., the most highly ranked interest scale for each individual). Together, these two approaches offer valuable quantitative information. Yet both methods provide little information about *why* interest scores do or do not converge from different measures. Hence, a third approach is needed to examine item content similarities and differences across inventories. We next discuss each method in greater detail and propose research questions for 1) correlation-based convergence, 2) high-point code convergence, and 3) item content convergence.

Correlation-Based Convergent Validity

Most previous research on the convergent validity of interest inventories has used correlation-based approaches with only two measures. A summary of past correlational studies is reported in the supplementary material (Table 8). The majority of these studies were found in inventory manuals, where convergent validity information is provided to show that a new interest measure is assessing the same intended constructs as an established measure. In particular, strong correlations among same-named scales across measures (e.g., Realistic-Realistic) indicate that participants who scored high on a RIASEC scale from one measure also score high on the same scale from another measure. Overall, past research indicates that cross-correlations among same- or similar-named interest scales are relatively high (r = .36-.81; r_{median} = .62).

Only one investigation has assessed convergent validity among more than two interest inventories (Savickas et al., 2002). This study reported moderate correlations (r = .36-.72, r_{median} = .59) among similar and same-named scales from the Strong Interest Inventory (SII), Self-Directed Search (SDS Form R), ACT Interest Inventory (UNIACT-R), Campbell Interest and Skills Survey (CISS), and Kuder Occupational Interest Survey (KOIS). The findings were interpreted as fair convergent validity. Nevertheless, the authors reported concerns about the generalizability of these results since the participants primarily consisted of career counselors and researchers attending the Society for Vocational Psychology conference. Thus, further research is needed to examine convergent validity among more typical interest inventory users.

There are also more advanced methods for evaluating correlation-based convergence than bivariate correlations. In particular, Campbell and Fiske’s (1959) development of multitrait-multimethod (MTMM) matrices strongly influenced how researchers assess convergent and discriminant validity. Confirmatory Factor Analysis (CFA) models can be applied to assess convergent and discriminant validity evidence from MTMM matrices. These models provide a method for estimating the independent effects (factor loadings) of method and trait latent factors on participant scores (Eid et al., 2006). Importantly, the CFA approach can overcome problems associated with MTMM such as its inability to quantify the extent of method or trait effects and inability to separate measurement and random error.

In this study, we use the recommended set of CFA models to assess the effect of interest traits and inventory methods on participant's RIASEC scale scores (Eid et al., 2006). Correlation-based convergent validity is assessed in these CFA models by comparing the variance explained by interest traits versus inventory methods. If interest traits explain considerably more variance in RIASEC scores compared to inventory methods, this provides evidence for convergent validity. Conversely, if inventory methods explain more variance in RIASEC scores than the traits themselves, this suggests a lack of convergent validity (Widaman, 1985). The strength of factor loadings from CFA models also provides information for comparing trait and method influences on differently named RIASEC scales. Thus, with the first set of analyses, we address the following research question:

Research Question 1. To what degree do interest trait and inventory methods affect respondents' RIASEC scale scores?

High-Point Code Convergence

High-point codes are a second important way of examining convergent validity among interest inventories. High-point codes, which reflect an individual's strongest interest area, are widely used in both practice and research. In career guidance settings, high-point codes are often used to focus individuals' career exploration efforts (Hanna & Rounds, 2020). High-point codes are readily interpretable for individuals across education levels, and they allow for direct linkage into occupations (Harmon et al., 1994). In research, high-point interests codes have been used to predict career choice (Hanna & Rounds, 2020) and outcomes within work environments, such as job satisfaction and performance (Hoff et al., 2020; Nye et al., 2017).

Despite their various uses, scarce research exists on the convergence of high-point codes from different inventories. To our knowledge, only one study has compared high-point codes from multiple measures (Savickas & Taber, 2006). This study found that, unlike the moderate degree of correlation-based convergence, RIASEC high-point codes were less consistent across interest inventories. Between pairs of the five interest inventories, exact three-letter high point code matches only occurred at the frequency of 3-15% (Savickas & Taber, 2006). Nevertheless, the study was conducted on the same dataset as Savickas et al (2002), and the unique sample characteristics limit the generalizability of findings. Thus, it is important to revisit and further investigate high-point code convergent validity.

A simple method for examining the convergence of high-point codes involves calculating the percent of participants who obtain the same high-point code on two inventories (Rounds et al., 2021). High percentages of high-point code matches indicate high convergent validity. Although there is no widely accepted benchmark for the percentages that would support convergence, guidance is available from past research on matched high-point codes from different versions of the same inventory. Specifically, the hit rate between the 30- and 60-item O*NET Interest Profiler is 69.2%, and the hit rate between the 60- and 180-item versions is 78.4% (Rounds et al., 2021). Comparatively, we would expect hit rates between inventories developed from different traditions to be lower. With the second set of analyses, we address the following research question:

Research Question 2. How well do high point codes agree across interest inventories?

Content-Based Convergent Validity

A third way to assess convergent validity is to systematically examine item content. The RIASEC categories comprise a heterogeneous set of work activities and environments, each encompassing a variety of narrower basic interests (Su et al., 2019). If item content varies substantially across inventories, the specific basic interests that comprise each RIASEC scale would also vary. Hence, differences in resulting interest scores among interest inventories may not reflect variability in individuals' interests, but rather variability in the content coverage of the RIASEC scales (Savickas & Taber, 2006). Despite the foundational importance of item content convergence for research findings to accumulate, content-based validity has received little attention in the field of interest measurement.

Item content is also especially important for career guidance. The accuracy and quality of career recommendations provided to individuals depends on the specific content of an inventory. For example, the Realistic scale of one inventory could be composed of mainly construction and engineering interest items, while another inventory could include mainly agricultural and outdoor interests. For an individual who enjoys building or engineering but is not interested in raising dairy cows or working as a park ranger, they would score high on Realistic using the first inventory but low on the second. Such difference in content coverage not only influences the client's Realistic score but could result in a different overall interest profile leading to different career recommendations.

Basic interests offer a systematic and effective way to examine item content in interest inventories because they are homogenous and have high face validity (Rounds, 1995). Items within each RIASEC scale can be organized into distinct basic interest dimensions which can be compared across measures. Comparing the basic interest coverage of RIASEC scales provides a deeper understanding of what is actually measured by different inventories, as well as the shared coverage among all measures. If a basic interest is consistently measured by all four inventories, it is central to the construct space of its corresponding RIASEC scale. On the contrary, if

RIASEC scales are composed of items from different basic interests, this would indicate a lack of consensus in their construct space. In this study, we use a recently proposed basic interest framework—the Comprehensive Assessment of Basic Interests (CABIN; Su et al., 2019)—to investigate item coverage. Our content-based analysis addresses the following question:

Research Question 3: Do items in different interest inventories reflect the same basic interests within RIASEC scales?

Summary of Study Aims

Our study addresses the fundamental question of whether different interest inventories provide similar information to individuals about their interests and how they connect to different careers. We examine this question with four interest inventories, using three complementary analytic approaches: 1) CFA approaches to model trait and method effects, 2) high-point code agreement, and 3) basic interest item coverage. Our study extends existing research by using a sample representative of typical interest inventory users. Moreover, our comparisons of the shared construct space of different inventories offer a new, systematic way to examine convergent validity in future research. Altogether, our study offers insights into the similarities and differences among RIASEC measures, providing theoretical and practical implications for the development of future interest inventories.

CHAPTER 2: METHOD

Participants

Participants were 327 undergraduates (approximately 80% were freshmen and sophomores) in a large midwestern university. All participants were enrolled in a career development course and are likely to be representative of students who would typically complete an interest inventory. Participants ranged in age between 17 to 23 years (approximately 80% were under age 20) and were relatively balanced in self-identified sex (43% male, 57% female). The students completed all four interest measures in partial fulfillment of a departmental course research requirement. The sample was initially collected for a dissertation, but it has not been included in published research (Russell, 2007).

Prior to data analysis, quality control items (embedded within the participants' response forms and designed to detect random or inattentive responses) were checked. Of 327 initial participants, 7 protocols were identified as suspect of careless responding, and were thus eliminated from the dataset. One participant did not complete the SDS, but other available responses were included in the dataset. This resulted in a final dataset sample size of 319.

Measures

The present study focuses on four RIASEC measures: Self-Directed Search (SDS; Holland, 1994), ACT Revised Unisex Interest Inventory (UNIACT; ACT, 1995), Interest Profiler Short Form (IP Short Form; Rounds et al., 2010) and Strong Interest Inventory (SII; Harmon, 1994). These four inventories were chosen because they are among the most-used interest inventories, and because they all include a set of scales that specifically measure the RIASEC constructs. Study participants granted permission for their interest inventory results from class to be combined with their responses to the other interest measures administered outside of class (i.e., the SII). Out of these four measures, we were able to obtain items from the SDS, UNIACT, and IP, but not the SII.

Self-Directed Search (SDS; Holland, 1985).

In the SDS, each RIASEC construct is evaluated by 11 activity items in Like/Dislike response format (e.g., repair cars), 11 Competencies items in Yes/No response format (e.g., I can repair furniture), 14 Occupations items in Yes/No response format (e.g., social worker), and 12 Self-Estimates items scoring from 1 (low) to 7 (high) (e.g., scientific ability). The SDS was scored by the researcher to obtain raw scores, according to instructions in the manual. For each participant, responses from all four aspects were used to calculate their interest scale scores and to identify their high-point interest code.

UNIACT-R Level 2 (UNIACT; Swaney et al., 1995).

The UNIACT Level 2 was designed to measure interests for college students and adults. It contains 90 activity items in total, with 15 items for each RIASEC scale (e.g., operate office machines). All items use the Dislike/Indifferent/Like response format. The UNIACT uses slightly different names for the RIASEC constructs than Holland's, but the scales are reportedly equivalent: R = Technical, I = Science, A = Arts, S = Social Service, E = Business Contact, C = Business Operations. The UNIACT was scored following instructions in the UNIACT Technical Manual (Swaney et al., 1995). Raw score values range from 15 to 45 and are converted to standardized T-scores (M = 50, SD = 10).

Interest Profiler Short Form (IP Short Form; Rounds et al., 2010).

The IP Short Form contains 60 activity items in total, with 10 items for each RIASEC construct (e.g., manage a retail store). All items use the Dislike/?/Like response format. Raw score values range from 0 to 120. We note that during the original data collection, all 180

Interest Profiler items were administered (Lewis & Rivkin, 1999). However, the IP Short Form is the primary form employed in current practice, so we derived the corresponding scores for the Interest Profiler Short-Form using the instructions found on O*NET (Rounds et al., 2010).

Strong Interest Inventory, (SII; Harmon, Hansen, Borgen, & Hammer, 1994).

The SII evaluates interests using 8 types of items and 317 items in total. Five item types are in the Dislike/Indifferent/Like response format: Occupations (135 items), School Subjects (39 items), Activities (46 items), Leisure Activities (29 items) and Types of People (20 items). Two item types ask participants to choose preferences between several options, including Activities (30 items) and Preferences in the Work World (6 items). Personal Characteristics items (12 items) are in the Yes/?/No response format. SII scale score data were taken from reports scored by the publisher, where raw score values were converted to standardized T-scores (M = 50, SD = 10; Harmon et al., 1994).

Data Analysis

Correlation-Based Convergent Validity

To address Research Question 1, we applied three sets of confirmatory factor analysis (CFA) models on the multitrait-multimethod (MTMM) correlation matrix. Model fit for all estimated models was evaluated using comparative fit index (CFI), Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). CFI and TLI values greater than .95 and RMSEA and SRMR values less than .05 suggest good/close model fit; CFI and TLI values greater than .90, RMSEA and SRMR values between .05 to .08 suggest fair/reasonable model fit; and models with RMSEA .08 and .10 indicate mediocre fit (Browne & Cudeck, 1993; Hu & Bentler, 1999).

First, we fitted a correlated-traits (CT) model. This model assumes that variances in observed interest scores are influenced by common latent trait factors and unexplained residual variances. For example, variances in Realistic scores from all four inventories are assumed to load on one common Realistic trait factor. This model is estimated to provide a baseline comparison for fit statistics of models that estimate both trait and method effects. Next, we fit a correlated traits-correlated methods model (CT-CM; Marsh & Grayson, 1995; Widaman, 1985), which assumes that variances in observed interest scores are influenced by both an interest trait and the inventory to which they belong. Traits were allowed to freely correlate, as were methods. No correlations are allowed between trait and method factors to estimate the independent effect of each source. Graphical representation for the CT-CM model is presented in Figure 1. Model fit statistics are compared between the CT and CT-CM model to indicate the importance of method effects.

Although the CT-CM model separately estimates trait and method effect, the influence of a general trait factor can be confounded by correlated method factors (Eid et al., 2008). Hence, we estimated a third set of CFA models—correlated traits-correlated methods-1 models (CT-C(M-1); Eid et al., 2003)—that offer an alternative view on interest trait and inventory method effects. Similar to the CT-CM model, these models estimate both trait and method effects. Unlike the CT-CM model, the CTC(M-1) model does not suffer from the existence of a potential general factor that can inflate the explained variance of method factors (Eid et al., 2006). The CT-C(M-1) model requires choosing one referent method as the standard for comparison. Because we do not assume one interest inventory to be the gold standard, we estimated four CT-C(M-1) models that each treat one inventory as the referent method. All models were specified and estimated using Mplus version 8.1 (Muthén & Muthén, 1998-2017).

High-Point Code Based Convergent Validity

To address Research Question 2, we examined the level of agreement among high-point codes for each participant on each measure. High point codes were assigned according to instructions in each inventory's manual. In general, this involved assigning a letter code based on the person's highest scores. Tied highest scores were randomly split to provide the respondent with a single high point code. Percentages of participants with matched high point codes between each pair of inventories were calculated. Agreement rates were also assessed using Cohen's Kappa (*K;* Cohen, 1960) and Fliess's Kappa, which takes into account the chance probability of high point code agreements (Fleiss, 1981). Kappa values above .60 indicates substantial agreement, values between .41-.59 indicate fair agreement, and values between .21-.40 indicate poor agreement (Fleiss, 1981).

Item Content-Based Convergent Validity

To address Research Question 3, four expert raters were asked to individually categorize all 366 items from three interest inventories (SDS, UNIACT, IP) into basic interest dimensions. The Strong Interest Inventory items are not open to the public domain and therefore were not included in content analyses. For the most contemporary representation of the interest space, we used the Comprehensive Assessment of Basic Interests (CABIN; Su et al., 2019). Each RIASEC domain contains 4 to 10 basic interests. The Realistic domain shows the highest level of complexity and covers 10 basic interests (*Agriculture, Animal Service, Athletics, Construction, Engineering, Mechanics/Electronics, Outdoors, Physical/Manual Labor, Protective Service, Transportation / Machine Operation*, Investigative covers 4 (*Life Science, Mathematics / Statistics, Medical Science, Physical Science*), Artistic covers 7 (*Applied Arts & Design, Creative Writing, Culinary Art, Media, Music, Performing Arts, Visual Arts*), Social covers 8

(*Health Care Service, Human Resources, Humanities & Foreign Language, Personal / Service, Religious Activities, Social Science, Social Service, Teaching Education*), Enterprising covers 8 (*Business Initiatives, Law, Management/Administration, Marketing/Advertising, Politics, Professional Advising, Public Speaking, Sales*), and Conventional covers 4 basic interests (*Accounting, Finance, Information Technology, Office Work*).

Four expert raters independently categorized all 366 RIASEC items into basic interests as specified in the Comprehensive Assessment of Basic Interest (CABIN; Su et al., 2019). Acceptable ($k > .60$) to good ($k > .80$; Gelfand & Hartmann, 1975; Landis & Koch, 1977) inter-rater agreement was found on all interest types, ranging from $k = .75$ for Conventional items to $k = .96$ for Investigative items. Final categorization for each item was determined based on the majority vote. A few items had equal votes for two separate categories, and they were counted as half an item to each category.

CHAPTER 3: RESULTS

Table 9 in the supplementary material displays means, standard deviations, and internal consistencies (Cronbach's alpha and McDonald's omega hierarchical) of interest scale scores for each inventory. We were not able to calculate internal consistency information for the Strong Interest Inventory because we do did have access to item-level data. The full multitrait-multimethod (MTMM) matrix is also reported in the supplementary material (Table 10). Next, we present results for the three research questions.

How Much Do Trait and Method Factors Affect RIASEC Scale Scores?

Table 1 summarizes Model fit statistics for the correlated-trait (CT) model, the correlated trait-correlated methods (CTCM) model, and the set of correlated trait-correlated methods - 1 (CTC(M-1)) Models. Together, these models investigated the degree of independent effects from interest trait and inventory method latent factors on participants' RIASEC scores. The CT model is the simplest model which assumes that variances in interest scores are only decomposed to the trait factor and residual error. It was used as a baseline comparison for models that include both trait and method factors. The CT model (*RMSEA* = .13, *CFI* = .80, *TLI* = .77, *SRMR* = .08) fitted the data poorly. The CTCM performed the best among the models tested and showed reasonable or good model fit across most fit indices (*RMSEA* = .09, *CFI* = .93, *TLI* = .90, *SRMR* = .06). The CTCM model also does not force our interpretation to be based on one interest inventory as the gold standard, but rather how well each inventory assesses each interest type. For these reasons, we retain and discuss factor loadings of the CTCM model.

Table 2 in the supplementary material shows the standardized estimates of factor correlations for both latent trait and method factors. Correlations among the RIASEC generally followed the expected pattern according to Holland's model—adjacent interest categories (e.g.,

r_{RI} = .39) were most highly correlated whereas opposite interest categories (e.g., r_{RS} = -.08) were weakly negatively correlated. Among latent method factors, the SDS showed the weakest correlation with other methods (*r's* = .04 - .08). The highest method factor correlation was observed among the IP and UNIACT (*r* = .26). Overall, the correlations among Method factors indicate that different inventories affected RIASEC scores in distinct ways (Eid et al., 2008).

Table 3 reports the standardized factor loadings for the traits and method factors, as well as residual variances. In general, the observed interest scores had higher loadings on latent RIASEC trait factors (range = .57-.93, mean = .77) compared to the latent inventory method factors (range = .25-.74, mean = .42). However, there were some differences in trait and inventory loadings. Across inventories, the UNIACT had lower loadings on the Realistic (λ = .57) and Social interest factors (λ = .62). The SII had lower loadings for Investigative (λ = .65), Enterprising (λ = .61), and Conventional (λ = .63) interest factors. Across RIASEC traits, interest scores from the SDS showed the strongest average loading on trait factors (.83), as well as the lowest average loading on method factors (.33). These findings coincided with results from the four CTC(M-1) models, among which the one using SDS as the reference method performed the best and met the criteria for acceptable model fit (*RMSEA* = .09, *CFI* = .92, *TLI* = .90, *SRMR* = .06). In sum, interest traits explained more variance in participants' scores than inventory methods in general. The choice of inventory method had stronger influence on the UNIACT and SII, whereas the SDS shared the most variance in interest traits with other interest inventories.

Do Respondents Receive the Same High-Point Code Across Interest Inventories?

Table 4 displays percentage of high-point code matches and Cohen's *k* agreement indices between RIASEC measures. Overall, using scores from two interest inventories, 41– 61% (*M* = 52%) of the participants were assigned the same high point code. This 52% hit rate is considerably lower than the hit rate observed between measures using different subsets of the same item pool (69-78%; Rounds et al., 2021). Correspondingly, there was poor (k = .34) to moderate (k = .45) Kappa agreement rates between pairs of inventories (mean = .40). Only two pairs—SDS-SII (63%; k = .51) and SDS-IP (61%; k = .49)—showed fair agreement. The UNIACT-SII pair showed the lowest level of agreement (40%; k =.27). We also calculated Fleiss' kappa (Fleiss, 1981) for multiple-rater (inventory) agreement, which also indicated that these four inventories showed poor high-point code agreement (k = .39). Thus, the high-point code comparison revealed weaker evidence for convergent validity compared to the correlational analyses.

The discrepancies in high-point codes could reflect inconsistencies in content coverage among inventories (Savickas & Taber, 2006). The RIASEC types are complex, multidimensional constructs, but RIASEC inventories are not always designed to reflect their multidimensionality. In other words, the RIASEC scales from different inventories could contain a different set of basic interests. We next conducted item content analyses for the SDS, IP, and UNIACT.

Do RIASEC Inventories Share Similar Content Coverage?

Table 5 shows the item count for each basic interest dimension in the three inventories. We classified basic interests based on their coverage: 1) Core basic interest dimensions are measured by 10% or more of the items in all three inventories; 2) Peripheral basic interests are measured by 10% or more items in two of the three inventories; and 3) Under-covered basic interests are measure by less than 10% items in at least two of the three inventories.

Figure 2 displays the percentage of items covering each basic interest averaged across the three inventories. It clearly shows that the core basic interests occupied large proportions of the construct space within each RIASEC—Realistic scale is mainly characterized by

Mechanics/Electronics and Construction/Woodwork; Investigative scale was mainly characterized by Physical Science; Artistic scale was mainly characterized by Music, Visual Arts, and Creative Writing; Social scale was mainly characterized by Teaching/Education, and Social Service; Enterprising scale was mainly characterized by Management/Administration, and Conventional scale was mainly characterized by Accounting and Office Work. The rest of the construct space consisted of peripheral basic interests distributed unevenly across the three inventories. For example, for measuring Investigative, the IP placed more emphasis on Medical Science, and the UNIACT placed more emphasis on Life Science. We also note that the SDS and UNIACT contained more broad items that cannot be categorized into basic interest categories, especially for Investigative (e.g., read scientific books or magazines), Social (e.g., I find it easy to talk with all kinds of people), and Enterprising scales (e.g., influence others). These items were put into the “other” category for each scale.

Table 6 summarizes the key findings about the basic interest coverage across inventories and RIASEC scales. The three inventories had reasonable consensus on the most essential (common) basic interests in each RIASEC category, as well as the least covered basic interests. Yet, the SDS, IP, and UNIACT each had different coverage of peripheral basic interests. In addition, 17 out of the 41 basic interest dimensions were missing or insufficiently covered in at least two of the inventories. For Realistic, there was no coverage for six basic interest scales: Engineering, Agriculture, Physical/Manual Labor, Athletics, Protective Services and Animal Services. For Investigative, only the SDS assessed Mathematics/Statistics. For Artistic, Culinary Art was not measured. For Social, Human Resources, Humanities & Foreign Language, and Religious Activities were missing, while only the SDS contained multiple items measuring Social Science and only the UNIACT covers Personal Service. For Enterprising, only the

UNIACT measured Professional Advising, whereas only the SDS measured Public Speaking. For Conventional, Information Technology was missing in all but the IP. Overall, these observed differential basic interest coverage provided implications for constructing new interest inventories as well as interpreting results from existing RIASEC measures.

CHAPTER 4: DISCUSSION

Vocational interest research and practice rests on a foundational assumption that different inventories assess the same latent constructs and provide similar career exploration information to individuals. The current study critically examined this assumption using four major interest inventories: the Self-Directed Search (SDS; Holland, 1994), ACT Revised Unisex Interest Inventory (UNIACT; ACT, 1995), Interest Profiler Short Form (IP Short Form; Rounds et al., 2010) and Strong Interest Inventory (SII; Harmon, 1994). We used three distinct methods to comprehensively assess convergent validity: 1) confirmatory factor analysis (CFA) modeling of multitrait-multimethod (MTMM) matrix, 2) high-point code agreement, and 3) item content coverage. Results from the first two analyses revealed that RIASEC scores from different measures were generally highly correlated, but there was poor high-point code agreement between pairs of inventories. Further, content analysis showed that interest inventories cover similar core basic interests, but there are also important nuances in the content of RIASEC scales within inventories. We next discuss each of these findings in greater detail and present implications for developing future inventories and interpreting existing measures.

RIASEC Scores Converged, but High-Point Codes Too Often Diverged

The two quantitative analyses each painted a distinct picture of convergent validity. First, we estimated correlated traits-correlated measures CFA models, which revealed that interest trait factors had stronger influences on RIASEC scores compared to inventory method factors. This provides evidence for convergent validity among the SDS, IP, UNIACT, and the SII. Nonetheless, the influence of methods factors on interest scores was also substantial— models with both trait and method factors had substantially better fit than the trait-only model. The rejection of the trait-only model suggests the final observed score is dependent not only on the trait assessed but the inventory used to assess the trait (i.e., there is a methods factor explaining variability in respondent's RIASEC scores; Eid et al., 2006).

The second method, high-point code analysis, revealed weaker evidence for convergent validity in each participant's highest RIASEC scores. Although this method is rarely used in examining convergent validity, high-point codes are widely used in vocational interest research and practice (Hanna & Rounds, 2020; Hansen, 2019). Thus, it is an important aspect of convergent validity to investigate. Our results indicated that if an individual took two RIASEC inventories, they would be assigned distinct high point codes about one in two times ($M_{\text{agreement}}$ = 52%), and consequently they would likely receive different career recommendations. This degree of matches between high-point codes is substantially lower than that observed from measures using different subsets of the same item pool (69-78%; Rounds et al., 2021).

Together, the results from the first two analyses emphasize the importance of assessing convergent validity in multiple, distinct ways. CT-CM methods effectively model the independent effects of traits and methods on scores, and they are helpful in assessing whether different methods are measuring the same underlying latent constructs (Eid et al., 2008). Yet, they do not provide a meaningful answer to whether different inventories yield the same results in practice. Inventories may be fairly robust in measuring the same underlying constructs, but subtle variations in item content can yield divergent results that lead to different high-point codes. Convergent validity research should take into consideration how scores are actually used and interpreted in practice. Otherwise, the real-world impact of using different measures to assess the same construct could be masked by high correlation-suggested convergence.

Item Content Analyses Revealed Convergence, Discrepancies, and Missing Domains

Item content is the basic unit that defines any latent psychological construct. Yet, it has received little attention in convergent validity literature that asks whether the same construct is being assessed by multiple methods. Our content analysis distinguished RIASEC scales into three parts: core, peripheral, and missing basic interests. The IP, the SDS, and the UNIACT mostly agree on the core basic interests within each RIASEC scale. This suggests that interest inventories have general consensus on what work activities and occupations are most typical of each RIASEC category. As noted, Figure 2 provides an overview of common basic interest dimensions within each RIASEC scale. This overview serves as a useful tool for researchers to understand what is currently being measured by major interest inventories.

Apart from the core basic interests, the three inventories each include distinctly different basic interest dimensions. We identified these scales as peripheral basic interests. Discrepancies in peripheral basic interests can lead to different overall representations of the RIASEC constructs, potentially explaining the low high-point code convergence among these inventories. For example, for respondents who enjoy physical science and mathematics, but are less interested in life or medical science, they may receive a higher Investigative score using the SDS compared to UNIACT. These differences in scores can lead to considerable variability when ranking RIASEC scores, especially when they share similar levels of interest in Investigative and other interest types. In other words, content differences in each scale can add up and ultimately give respondents different high point codes.

Lastly, we found that a large number of basic interests (17 of 41) are completely missing or insufficiently represented in current RIASEC measures. One possible reason for the incomplete representation of basic interests is that some basic interests reflect more than one RIASEC category. For example, Social Science captures both Investigative and Social types (Su et al., 2019), and Human Resources captures a mix of Social and Enterprising. Including basic interests that tap into more than one RIASEC category can affect the structure of Holland's model, which is an important quality in RIASEC inventories (Rounds & Day, 1999). However, as a growing number of jobs require an intersection of multiple interest types, ignoring basic interests hinders the effectiveness of interest inventories for providing career guidance.

Implications for Developing New Interest Inventories and Applications

Our content analysis offers applied implications for constructing new interest inventories and interpreting results from existing ones. In an ideal situation, researchers should strive to measure the full range of basic interests. However, this is unrealistic in many cases, and it is more practical to selectively include basic interests. Therefore, we give three general recommendations on constructing basic interest-based inventories that are more adaptive to the targeted clientele and better capture their corresponding labor market.

First, to provide career or educational guidance for students, we suggest including core basic interests with the addition of basic interests that best correspond to important instructional programs. For example, including all basic interests under the Investigative type is desirable because they can be directly linked to college majors. To offer career guidance for the general public, we suggest including basic interests that map onto fast-growing occupations in the workforce. For instance, according to the U.S. Bureau of Labor Statistics (BLS), retail trade and healthcare each make up roughly 10% and 12% of the service-providing industry (BLS, 2021). Therefore, it is important to include sales and healthcare service dimensions in interest measurement. Another example is Information Technology, which connects to computer and mathematical occupations and is projected to grow 12% by 2029 (BLS, 2021).

Second, we offer a few cautionary notes for interpreting existing interest results in applied settings. Practitioners can benefit by considering the characteristics of target clients for choosing an RIASEC inventory to administer, especially if individuals might have high interest in areas outside of the core basic interest dimensions within the RIASEC. Knowing which basic interests an inventory does not include can allow practitioners to supplement an inventory with basic interests from another scale. Alternatively, basic interests can be used in a multi-step approach to fine tune or provide more certainty in recommendations. Meanwhile, interest inventory users should be made aware that interest inventories are not interchangeable—if they receive different high point codes from two inventories over time, it does not necessarily reflect true changes in their interests. These cautionary notes are especially important as more people take online interest inventories for career self-exploration. Websites that provide interest assessment should include relevant information about which basic interests are being measured (and those not being measured) to help individuals correctly interpret their interest results.

Third, for researchers, it is important to consider differences between inventories when including interest scales in studies. Differences in item content from inventories can yield different scale scores and consequently different study results. For example, previous research suggests variability between interest inventories when examining their fit to Holland's circumplex, which results in different degrees of structural validity (Armstrong et al., 2003; Rounds & Tracey, 1995; Tracey & Rounds, 1993). Previous meta-analyses on the criterion validity of vocational interests also suggest differences in validities obtained from different measures. For example, the relations between interest fit with task performance ($\rho = .20$ to $.31$; Nye et al., 2017) and interest fit and job satisfaction ($\rho = .11$ to $.24$; Hoff et al., 2020) vary depending on the inventory. Accordingly, researchers should be aware of what basic interests different inventories include for selecting the most relevant measure. For example, using only the IP to assess the interests of financial analysts would fail to assess measure the basic interests most likely to be relevant to the sample (i.e., finance and statistics/mathematics). To address this, the researcher could supplement the interest measures with finance and statistics scales from a public domain basic interest inventory (e.g., Liao et al., 2008).

Strengths, Limitations, and Future Directions

To our knowledge, the current study is the most comprehensive assessment of convergent validity among vocational interest inventories. We quantified the degree of convergence among major interest inventories using correlation-based and high point code-based approaches, and we also examined content similarities and differences across RIASEC scales. Each method revealed distinct aspects of interest measurement that together provide important implications for understanding what is being measured by RIASEC inventories. However, there are several noteworthy limitations of the current research.

First, for our quantitative analysis, we selected four major interest inventories; however, there are other interest inventories that we did not analyze (e.g., Tracey, 2002). Future content validity studies on interest measurement could benefit from analyzing a wider selection of publicly accessible interest items from reputable inventories, particularly in examining the consistency of core basic interest dimensions identified in the current study. Second, instead of differential coverage, the reported low high-point code agreement could reflect other divergent approaches involved in the development of each inventory. Interest inventories can differ in a variety of way, including item selection to reduce sex differences, the use of normed vs raw score reporting, items written for different levels of education, and item type (e.g., occupations, activities, school subjects). For example, the UNIACT selected items with the smallest sex differences, which potentially explains its stronger method effect on Realistic and Social interests, the two scales with the largest sex differences (Su et al., 2009). Future studies could further assess effects of specific elements on convergent validity among interest scores.

Third, there is currently no uniform consensus on the number and structure of basic interests, and the results of item content analysis could change if a different set of basic interest dimensions were used. Hence, our content analysis results, which are based on the Comprehensive Assessment of Basic Interest (CABIN; Su et al., 2019), should be interpreted as constructive, not definitive. As the world of work changes, vocational interest inventories must update their representation of interest dimensions through bottom-up processes, capturing the types of jobs most relevant in the present and future. In addition, all methods of construct validity, including content and convergent validity, should be regularly assessed to keep interest inventories up to date.

Conclusion

The current study assessed convergent validity among major interest inventories using three methods, each providing distinct contributions to better understanding interest measurement. The results showed that major interest inventories reflect similar RIASEC traits in general, but they less often provide consistent high-point code to respondents. Correspondingly, interest inventories reached consensus on core basic interest dimensions within each RIASEC type, but they each have distinct coverage of peripheral basic interests. Overall, our findings have methodological implications for assessing convergent validity and help integrate theoretical understanding of the RIASEC constructs with important implications for future research.

TABLES & FIGURES

Table 1.

Fit Statistics for Confirmatory Factor Analysis Models

	Chi-square	*df*	*RMSEA*	*CFI*	*TLI*	*SRMR*
CM	5413.12	246	.26	.17	.07	.22
CT	1524.83	237	.13	.80	.77	.08
CTCM	683.12	207	.09	.93	.90	.06
CTC(M-1)						
SDS-referent	738.29	216	.09	.92	.90	.06
IP-referent	829.76	216	.09	.90	.88	.08
UNI-referent	860.51	216	.10	.90	.87	.09
SII-referent	950.99	216	.10	.89	.86	.15

Note. SDS = Self-Directed Search; IP = Interest Profiler (Short-Form); UNIACT = the Unisex ACT Interest Inventory; SII = Strong Interest Inventory; CT = Correlated Trait model; CTCM = Correlated trait-Correlated method model; CTC(M-1) = Correlated trait-Correlated method minus one model.

Table 2.

Correlations among Latent Trait and Method Factors

	Trait Factors				
	R	I	A	S	E
I	.39				
A	.10	.12			
S	-.08	.07	.17		
E	-.07	-.10	.06	.20	
C	-.01	-.06	-.17	-.05	.32
	Method Factors				
	SDS	IP	UNI		
IP	.05				
UNI	.08	.26			
SII	.04	.12	.18		

Note. SDS = Self-Directed Search; IP = Interest Profiler (Short Form); UNIACT = the Unisex ACT Interest Inventory; SII = Strong Interest Inventory. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; C = Conventional.

Table 3.
Standardized Parameters for the Correlated Traits-Correlated Methods (CTCM) Model

	R	I	A	S	E	C	Row Mean
	Loadings on Trait Factors						
SDS	.93	.80	.84	.85	.82	.72	**.83**
IP	.77	.84	.84	.84	.77	.74	**.80**
UNIACT	.57	.79	.87	.62	.81	.87	**.75**
SII	.81	.65	.71	.73	.61	.63	**.69**
Column Mean	**.77**	**.77**	**.81**	**.76**	**.75**	**.74**	**.77**
	Loadings on Method Factors						
SDS	.25	.30	.25	.31	.31	.54	**.33**
IP	.46	.43	.36	.37	.42	.44	**.41**
UNIACT	.74	.46	.35	.45	.34	.35	**.45**
SII	.45	.51	.44	.46	.57	.63	**.51**
Column Mean	**.48**	**.43**	**.35**	**.40**	**.41**	**.49**	**.42**
	Residual Variances						
SDS	.08	.27	.24	.17	.23	.19	**.20**
IP	.19	.12	.16	.16	.23	.27	**.19**
UNIACT	.13	.17	.13	.41	.24	.12	**.20**
SII	.15	.32	.30	.25	.31	.21	**.26**
Column Mean	**.14**	**.22**	**.21**	**.25**	**.25**	**.20**	**.21**

Note. SDS = Self-Directed Search; IP = Interest Profiler (Short Form); UNIACT = the Unisex ACT Interest Inventory; SII = Strong Interest Inventory. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; C = Conventional.

Table 4.

Percentage of High Point Code Match and Cohen's k Agreement Indices Among Inventories

	IP	SDS	UNIACT	SII
IP	--	61%	51%	50%
SDS	.49	--	46%	63%
UNIACT	.39	.35	--	40%
SII	.36	.51	.27	--

Note. Fleiss' kappa for overall agreement k = .39. Above diagonal are percentage of participants who have matched high point codes between pairs of inventories. Below the diagonal are Cohen's k index of agreement. k values between .41-.59 indicates fair agreement whereas k values between .21-.40 indicates poor agreement.

Table 5.

Item Count for Basic Interest Categorization and Interrater Agreement

	IP		SDS		UNIACT	
REALISTIC (*k* = .80)						
Mechanics/Electronics	5	50%	13	36%	6	43%
Agriculture	1	10%	1.5	4%	0	0%
Construction/Woodwork	2	20%	15	42%	4	29%
Transportation/Machine Operation	1	10%	2.5	7%	1	7%
Outdoors/Nature	1	10%	3	8%	2	14%
Protective Service	0	0%	1	3%	0	0%
Others	0	0%	0	0%	2	14%
Investigative (*k* = .96)						
Life Science	1	10%	6	17%	6	43%
Physical Science	5	50%	11	31%	4	29%
Medical Science	3	30%	1	3%	2	14%
Mathematics/Statistics	0	0%	5	14%	0	0%
Others	1	10%	13	36%	3	21%
Artistic (*k* = .80)						
Media	1.5	15%	3	8%	1	7%
Applied Arts & Design	1	10%	2.5	7%	1.5	11%
Music	3	30%	12	33%	5	36%
Visual Arts	2	20%	6	17%	3.5	25%
Performing Art	1	10%	4	11%	1	7%
Creative Writing	1.5	15%	7	19%	3	21%
Others	0	0%	1.5	4%	0	0%
Social (*k* = .78)						
Teaching/Education	4	40%	8.5	24%	2	14%
Social Science	0	0%	6	17%	1	7%
Personal Service	0	0%	2	6%	2	14%
Social Service	5	50%	14.5	40%	4.5	32%
Human Resources	0	0%	1	3%	0	0%
Health Care Service	1	10%	2	6%	2	14%
Others	0	0%	2	6%	3.5	25%
Enterprising (*k* = .76)						
Management/Administration	4	40%	10	28%	3	21%
Business Initiatives	2	20%	2	6%	2	14%
Marketing/Advertising	1	10%	1	3%	1	7%
Professional Advising	0	0%	0	0%	2	14%
Public Speaking	0	0%	4	11%	0	0%
Sales	1	10%	10	28%	1	7%
Politics	1	10%	2	6%	2	14%
Law	1	10%	0	0%	2	14%
Others	0	0%	7	19%	2	14%
Conventional (*k* = .75)						
Finance	0	0%	5.5	15%	4.5	32%
Accounting	2.5	25%	11.5	32%	6.5	46%
Information Technology	2	20%	3	8%	0	0%
Office Work	5.5	55%	14	39%	4	29%
Others	0	0%	2	6%	0	0%

Note. SDS = Self-Directed Search; IP = Interest Profiler (Short Form); UNIACT = the Unisex ACT Interest Inventory.

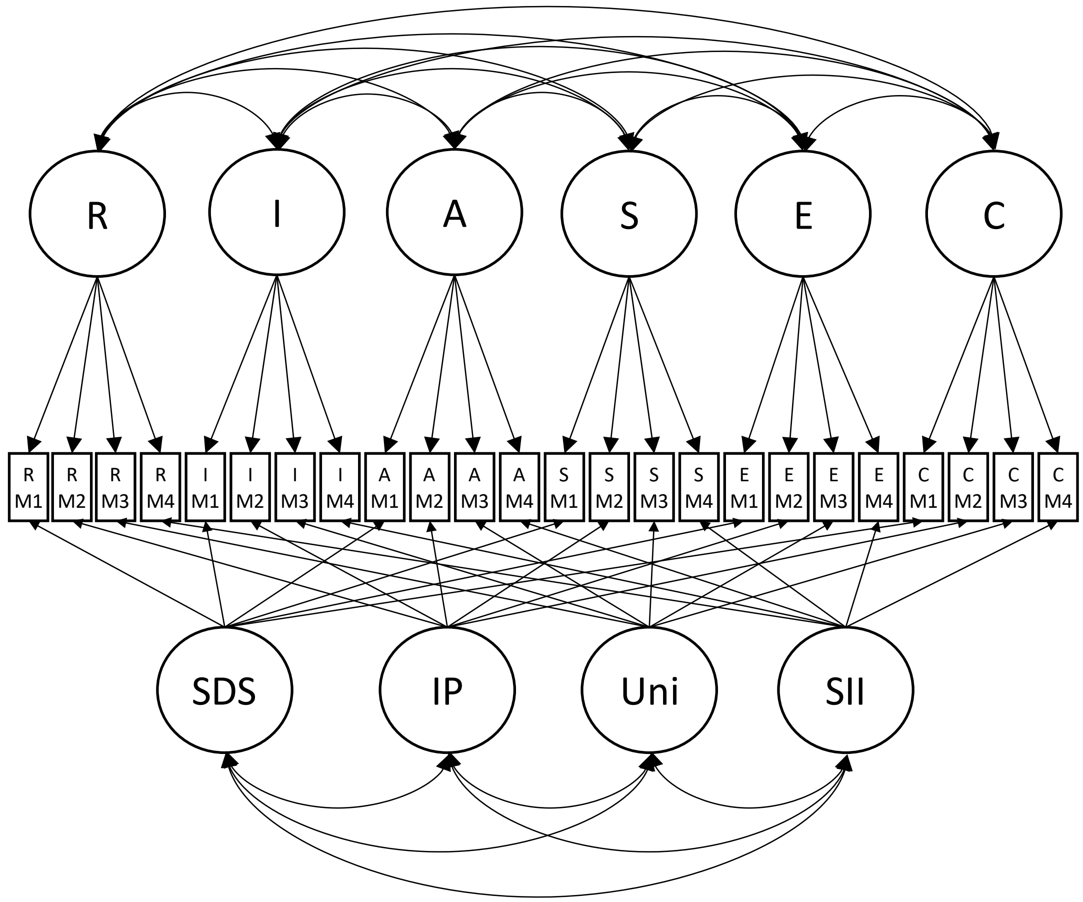
Table 6.
Summary of Content Analysis Findings

	Core Basic Interests	Peripheral Basic Interest	Under-Covered Basic Interest
Realistic	Mechanics/Electronics, Construction/Woodwork	Transportation/Machine Operation, Outdoors/Nature	Engineering, Agriculture, Physical/manual labor, Athletics, Protective Service, Animal Service
Investigative	Physical Science	Life Science, Medical Science	Mathematics/Statistics (SDS)
Artistic	Music, Visual Arts, Creative Writing	Media, Applied Arts & Design, Performing Art	Culinary Art
Social	Teaching/Education, Social Service	Health Care Service	Social Science (SDS), Personal Service (UNIACT), Human Resources, Humanities & Foreign Language, Religious Activities
Enterprising	Management/Administration	Business Initiatives, Sales, Politics, Law	Professional Advising (UNIACT), Public Speaking (SDS), Marketing/Advertising
Conventional	Accounting, Office Work	Finance	Information Technology (IP)

Note. Core Basic Interests are measured by 10% or more of items in all three inventories (SDS, UNIACT, IP); *Peripheral Basic Interests* are measured by 10% or more of items in two of the three inventories; *Under-Covered Basic Interests* are measured by 10% or less of items in at least two inventories, and if a basic interest is measured by 10% or more items in one inventory, the specific inventory is noted in parentheses.

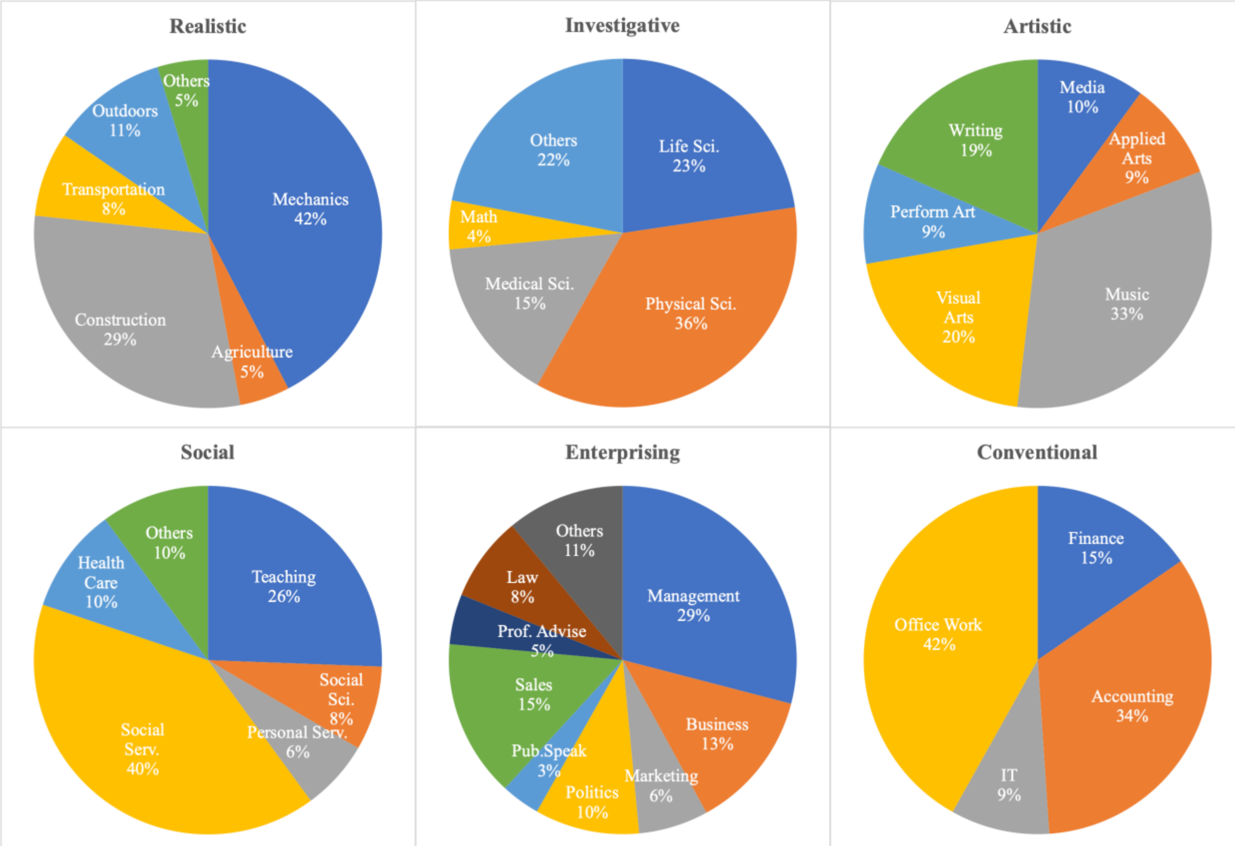
Figure 1.

Correlated Trait – Correlated Method (CTCM) Model of RIASEC Inventory Convergence



Note. SDS = Self-Directed Search; IP = Interest Profiler (Short Form); UNIACT = the Unisex ACT Interest Inventory; SII = Strong Interest Inventory. M1 to M4: different inventories 1 to 4.

Figure 2.
Averaged Percentage of Items Belonging to Basic Interests



SUPPLEMENTARY TABLES

Table 7.
Descriptions for RIASEC types

	Preference for Activities	Example activities	Example occupations
Realistic	Explicit, ordered, or systematic manipulation of objects, tools, machines, and animals	Repair cars; Build things with wood; Raise dairy cows	Auto mechanic; Truck driver; Civil engineer; Firefighter
Investigative	Observational, symbolic, systematic, and creative investigation of physical, biological, and cultural phenomena in order to understand and control such phenomena	Work with a chemistry set; Take mathematics course; Work in a laboratory	Physicist; Astronomer; Anthropologist; Research Scientist
Artistic	Ambiguous, free, unsystematized activities that entail manipulation of physical, verbal, or human materials to create art forms or products	Sketch, draw, or paint; Practice a musical instrument; Act in a comedy or play	Artist; Singer; Actor; Novelist
Social	Manipulation of others to inform, train, develop, cure, or enlighten	Teach in a high school; Help handicapped people; Take Human Relations course	High school teacher; Physical therapist; Social worker; Vocational counselor;
Enterprising	Manipulation of others to attain organizational goals or economic gain	Sell something; Supervise the work of others; Operate a business	Salesperson; Business executive; Store manager; Advertising executive
Conventional	Explicit, ordered, systematic manipulation of data	Fill out income tax forms; Set up a record system; Take an inventory of supplies or products	Accountant; Bookkeeper; Financial analyst; Payroll clerk

Table 8.
Cross-Correlation Between Similar or Same-Named Interest Scales

Inventory 1	Inventory 2	Cross Correlation	N	Gender	Sample Description	Source
IP Long Form	Interest Finder	.79	1061	56% F	Representative Sample from Four U.S. States	Rounds, Walker, Day, Hubert Lewis & Rivkin, 1999
IP Short	Interest Finder	.77	1061			Rounds, Su, Lewis & Rivkin, 2011
IP	SII	.64	313	65% F	College Students	Armstrong, Allison, & Rounds, 2008
ACT-VIP	SVIB	.81	62	100% M	Male College Seniors	Hanson, 1974
ACT-VIP	SVIB	.78	83	100% F	Female College Seniors	Hanson, 1974
ACT-VIP	SVIB	.72	126	100% F	Female College Freshman	Hanson, Lamb, & English, 1974
ACT-VIP	SCII	.68	91	60% F	High School Seniors	Fabry, Blake& Seran, 1978
ACT-VIP	VPI	.53	338	43% F	11th graders	Lamb & Prediger, 1981
ACT-VIP	KGIS	.44[a]	243		9th graders	Lamb & Prediger, 1981
ACT-VIP	OVIS	.52[a]	271		9th graders	Lamb & Prediger, 1981
VPI	SVIB	.62	93		College Students	Blakeney, Matteson, & Holland, 1972
SII	SDS	.72	118	76% F	Career counseling practitioners and professionals who attended the Society for Vocational Psychology conference	Savickas, Taber & Spokane, 2002
SII	UNIACT	.65				
SII	CISS	.62[a]				
SII	KOIS	.42[a]				
SDS	UNIACT	.59				
SDS	CISS	.54[a]				
SDS	KOIS	.42[a]				
UNIACT	CISS	.46[a]				
UNIACT	KOIS	.36[a]				
CISS	KOIS	.37[a]				

Note. IP = Interest Profiler; SII = Strong Interest Inventory; ACT–VIP = ACT Vocational Interest Profile (1971 - 1974); SVIB = Strong Vocational Interest Bank; SCII = Strong-Campbell Interest Inventory; VPI = Vocational Preference Inventory; KGIS = Kuder General Interest Survey; OVIS = Ohio Vocational Interest Survey; CISS = Campbell Interest and Skills Survey; KOIS = Kuder Occupational Interest Survey; UNIACT-R = Revised Unisex ACT Interest Inventory (1995).
[a] Mean within corresponding scales are calculated first before averaging across scales.

Table 9.
Descriptive Statistics on Interest Scale Scores

	SII		UNIACT				IP				SDS			
	M	*SD*	*M*	*SD*	*Alpha*	*Omega*	*M*	*SD*	*Alpha*	*Omega*	*M*	*SD*	*Alpha*	*Omega*
R	42.23	9.37	48.2	9.78	.87	.64	10.74	12.79	.88	.73	17.88	11.37	.95	.81
I	40.93	8.31	48.81	9.43	.92	.73	23	15.19	.86	.68	21.17	9.59	.91	.78
A	44.31	9.09	51.68	9.71	.87	.63	30.38	15.69	.83	.62	24.1	10.65	.91	.60
S	49.48	10.84	50.6	11.13	.83	.56	30.4	15.98	.80	.57	31.39	10.54	.93	.66
E	51.81	10.71	53.28	9.99	.87	.70	25.19	12.91	.78	.52	30.98	10.53	.92	.65
C	47.19	9.7	50.16	9.05	.92	.64	18.05	15.18	.85	.76	21.93	9.73	.93	.67

Note. SDS = Self-Directed Search; IP = Interest Profiler (Short Form); UNIACT = the Unisex ACT Interest Inventory; SII = Strong Interest Inventory. R = Realistic; I = Investigative; A = Artistic; S = Social; E = Enterprising; C = Conventional.

Table 10.

Multi-trait Multi-method (MTMM) Matrix

	IP_R	IP_I	IP_A	IP_S	IP_E	IP_C	SD_R	SD_I	SD_A	SD_S	SD_E	SD_C	U_R	U_I	U_A	U_S	U_E	U_C	SI_R	SI_I	SI_A	SI_S	SI_E
IP_R	.55																						
IP_I	.24	.30																					
IP_A	.03	.26	.30																				
IP_S	.08	.04	.22	.30																			
IP_E	.27	.09	.01	.08	.37																		
IP_C	**.78**	.48	.21	.00	-.04	.50																	
SD_R	.36	**.74**	.32	.09	-.07	.58	.40																
SD_I	.53	.52	**.76**	.91	.38	-.09	.48	.07															
SD_A	-.03	.09	.66	**.77**	.21	.02	-.05	.05	.99														
SD_S	-.05	-.09	.05	.69	**.64**	.25	.04	-.01	.05	.28													
SD_E	.02	-.05	-.10	.07	.36	**.66**	.04	.35	-.06	.59	.48												
SD_C	**.76**	.53	.35	.21	.44	.25	**.65**	.33	.23	.05	-.03	.05											
U_R	.48	**.84**	.29	.26	-.07	.04	.41	**.69**	.93	.34	-.49	-.08	.58										
U_I	.21	.36	**.85**	.31	.85	-.04	.80	.72	**.76**	.98	.03	-.89	.38	.37									
U_A	.21	.31	.33	**.66**	.27	.06	.40	.43	.27	**.59**	.23	.03	.37	.34	.40								
U_S	.00	.03	.23	.33	**.69**	.37	-.05	.10	.33	.32	**.70**	.48	.04	.00	.74	.49							
U_E	.36	.01	-.06	.04	.48	**.75**	.05	.05	-.33	.00	.46	**.70**	.20	-.03	-.67	.07	.55						
U_C	**.74**	.56	.26	.03	.09	.20	**.79**	.41	.35	-.08	.06	.01	**.65**	.45	.24	.84	.04	.40					
SI_R	.35	**.64**	.66	.55	.07	.26	.32	**.71**	.04	.04	.00	.07	.37	**.58**	.89	.21	.06	.76	.57				
SI_I	.06	.21	**.66**	.31	.23	-.09	-.03	.07	**.71**	.27	.08	-.10	.24	.27	**.71**	.36	.21	-.10	.99	.26			
SI_A	.09	.69	.23	**.72**	.24	.09	-.03	.07	.69	**.69**	.70	.08	.72	.73	.25	**.58**	.29	.04	.35	.24	.44		
SI_S	.05	.02	.53	.20	**.67**	.30	.00	.06	.07	.68	**.58**	.34	.54	-.03	.24	.26	**.55**	.40	.93	.74	.30	.34	
SI_E	.26	.08	.06	.06	.46	**.66**	.06	.68	-.06	.04	.34	**.58**	.93	.00	-.03	.20	.40	**.67**	.30	.36	.65	.22	.60

Note. IP = Interest Profiler; SD = Self-Directed Search; U = Revised Unisex ACT Interest Inventory; SI = Strong Interest Inventory.

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